A framework for assessing uncertainty in ecosystem models

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Abstract: In addition to their use as research tools, ecosystem models have been used more frequently in the last two decades to support policy decisions and inform stakeholder consultations. Models have been central to the work of the Intergovernmental Panel of Climate Change (IPCC) and the International Geosphere-Biosphere Programme (IGBP). The usefulness of results from model simulations for any purpose is determined by their quality like the uncertainty accompanying model outputs. In model evaluation, however, a broad variety of different approaches to define uncertainty still exists and these have not, so far, been standardized. In contrast, field research has already defined standard uncertainties. Here, we define uncertainty based on statistical methods like standard deviation of a number of independent measurements as type A uncertainty, and define uncertainty based on scientific judgement as type B uncertainty. We are proposing three further categories of model uncertainty. Baseline uncertainties that originate from type A and B uncertainties in measurements used to determine inputs to the model are termed type C uncertainties. Further uncertainty arises from the scenarios constructed to run the model, which cannot be defined precisely. This category of uncertainty named type D uncertainty includes that element of future scenarios that cannot be predicted. Uncertainty also arises from not knowing precisely the true value of internal parameters of the model equations; this is referred to as type E uncertainty. Here we propose an experimental framework for harmonisation of uncertainty and sensitivity analyses of ecosystem models. The heuristic framework is based on standardised protocols for a general ecosystem model interface. The interface is part of an experimental client-server environment, which will allow common access to model experiment results for the research community, stakeholders and decision makers.

Keywords: uncertainty; ecosystem models; framework; standardisation

1. INTRODUCTION

In the last two decades, ecosystem models have changed from being pure research tools to improve process understanding, to providing support systems for informing policy decisions and stakeholder consultations (IPCC, 2001). Consequently the requirements concerning quality control and uncertainty assessment has also changed. The main problem in making this transition results from the philosophy of model development as pure research tools. Models, often designed by one researcher or a small research group to explore specific scientific problems (e.g. DNDC (Li et al. 1994), CENTURY (Parton et al. 1994), PaSim (Riedo et al. 1998) ROTHC (Jenkinson 1992)) are then extended to address emerging questions. Thus ecosystem models are heterogeneous in both structure and in the fundamental principles upon which they are based. This heterogeneity means that models need extensive testing and comparison (e.g. Smith et al., 1997) in order to understand effect of different model approaches on the accuracy of the results. However, there are no cross site, cross model comparisons that used evaluation protocol to explicitly explore the effect of model structure on uncertainty in the model results. This becomes a problem if model results are used to evaluate future developments as a basis for "real world" decisions. Model results in such a context are only meaningful if they are accompanied by measures of quality. An important measure of quality is the output uncertainty arising from model input uncertainty or from internal parameter uncertainty. Currently, there are number of tools for uncertainty and sensitivity analysis which are already used for different types of analysis (e.g. SIMLAB Saltelli (2004), GEM-SA (http://marc-kennedy.staff.shef.ac.uk/code.html) , SimEnv (Flechsig et al., 2005)). However, even if they are effective for certain case studies, they are not designed to offer off-the-shelf evaluation protocols to allow *ad hoc* cross-site and cross-model evaluation. This leads to a lack of comparability of model experiment results for the research community and more importantly, for the stakeholder and decision maker.

In meteorological field research, however, there are different types of standard measures of uncertainties. They define type A uncertainty to be based on statistical methods like standard deviation of a number of independent measurements, where type B uncertainty originates from scientific judgement using all relevant available information. Both types combined or individual give a certain measure of quality as described by the ISO (1995). In modelling, a broad variety of different approaches to analyse and to define uncertainty on model results exists (e.g. Satelli 2000, Hamby 1994). They differ in their capacity to describe quality and a definition of standards is inevitable.

This problem was addressed during a workshop at Aberdeen University (UK) (http://www.abdn.ac.uk/modelling/cost627/index.htm) in 2004. The result was an analysis of the current situation and an attempt to standardise model uncertainty analysis. The preliminary recommendations and tools are presented in this paper.

2. METHODS

2.1 Heuristic approach

In this concept, a group of experts from the target research area are integrated into the process to test and evaluate concepts, in multiple workshops representing a heuristic approach. This process aims to maintain a community-evaluated development with a strong focus on applicability. In the course of concept development, the experts are able to present the results within their home research environment to detect possible problems. This feedback flow is used for the further refinement of the concepts. A heuristic approach sustains a constant flow of information to develop a problem-focused concept. The EU-funded COST 627 programme has supported a multiple workshop series, followed by a meeting in 2005.

2.2 Questionnaires

Questionnaires were distributed during the meeting and 14 returns were used to compile the results. The questions asked were: "In the following table, you will find a number of input factors that are commonly used in most of the workshop models. Please give your impression of the uncertainty associated with defining these model inputs". We explicitly asked for type B uncertainty as we where not referring to specific measurements. The participants were asked to declare themselves as modellers or field researchers or both, so the results could be analysed accordingly. This exercise was a first attempt at exploring type B uncertainty associated with model input factors using a questionnaire.

3. RESULTS

3. 2 Definition of Uncertainty

The workshop led to the proposal of three types of model uncertainties. Referring to the ISO (1995) guide we classify them C, D and E type. The type C uncertainty, called baseline uncertainties, originates from type A and B uncertainties associated with measurements used to determine the input factors of a model, and the propagation of these uncertainties through the model. Input factors are defined to be all values that feed into the model, such as initial values, driving variables etc. Type D, or scenario uncertainties, are related to predictive processes in modelling. They incorporate type C uncertainty, accompanied by the uncertainty in the prediction of future environmental conditions such as climate and their interaction with ecosystems. In contrast to type C and D uncertainty, which treat the model as a black box, type E, or conceptual uncertainty, refers to the internal parameters of the of model equations such as rate constants and threshold values used in the model. Figure 1 shows the main characteristics of the different types of uncertainty and how they are related.

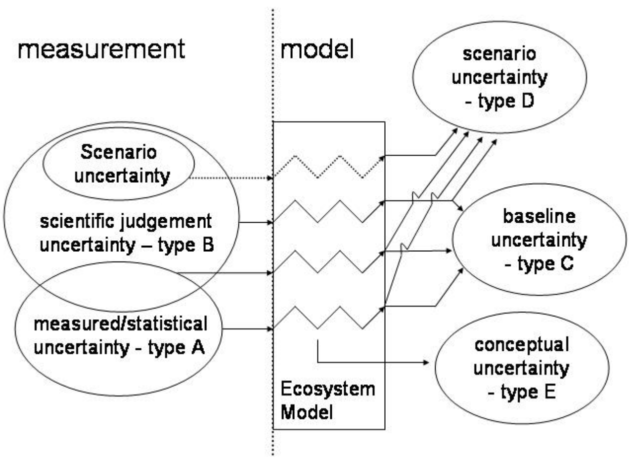

Figure 1. concept of uncertainty and propagation from measurement to modelling

3.3 Questionnaire results

The results from the questionnaire of the Aberdeen workshop (n=14) are shown in table 1.

Input factor	Uncert-ainty range - modeller	Uncert-ainty range - field-researcher	Uncert-Ainty range - both
Air temperature	0.1-0.5°C	0.1-2.0 °C	0.5 -1.0°C
Soil temperature	0.1-1.0°C	0.1-2.0°C	0.5-5
Precipitation	0.1-2mm	1-3mm	1-2mm
Atmospheric CO_2	5ppm	1-10ppm	1ppm
Global radiation	1-10W/m2	30 W/m2	10 W/m2
Clay content	15%	1-25%	6-30%

Table 1. Selected results of estimated uncertainties from expert questionnaire respondents (n = 14) more values can be found under http://www.abdn.ac.uk/modelling/cost627/Questionnaire.htm .

3.4 Conceptual framework implementation

In order to address the problem of a lack of availability of model experiment results addressing uncertainty for the research community, stakeholders and decision makers, a general framework approach has been developed.
The focus is on central services for uncertainty and sensitivity analyses incorporating platform independent interfaces to provide access to related methods and datasets. This framework approach includes:

- Standardized methods for uncertainty and sensitivity analysis for ecosystem models, including techniques for cross-site comparison.
- Standardized datasets to allow inter-model comparison of uncertainty and sensitivity measures.
- Standardized software interfaces for ecosystem models to allow access to databases for model experiments and results.
- Databases for model evaluation results to allow scientists, stake-holders and policy maker's easy

access to information of model quality and uncertainty.

To implement the approach we propose a web-based client - server architecture (figure 2).

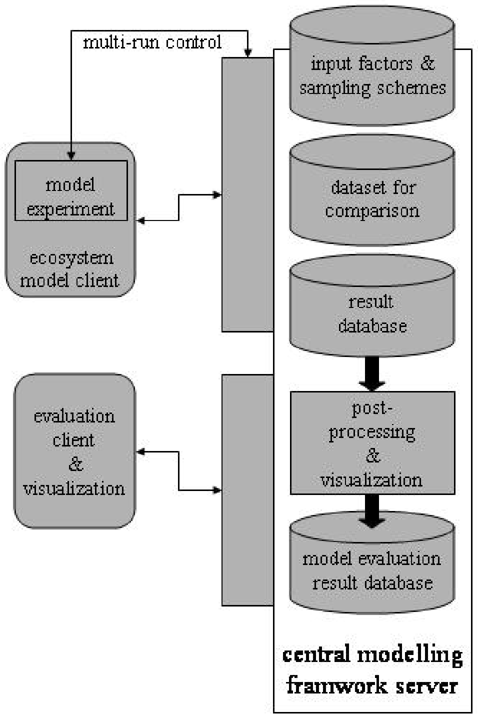

Figure 2. framework concept

- Site standardization: Server-based datasets of input factors at standardized reference sites to allow inter-model comparison of uncertainty and sensitivity measures
- Experiment design: Server based standardised sampling schemes for different uncertainty and sensitivity techniques (global and local methods, deterministic and random schemes)
- Experiment performance: Client based automated multi-run simulation experiments and result transfer to the server
- Experiment post-processing: Server based interactive and standardized experiment analysis including output aggregation and transformation, reference data comparison; determination of uncertainty and sensitivity measures and their visualisation
- Result dissemination / outreach: Server based database to store and retrieve model evaluation results with profiles for different user groups like stakeholders and policymakers, model scientist and field researchers.

Figure 3 exemplifies the graphical expressions of uncertainty from a cross model comparison pre-study using the DNDC and PASIM model (Gottschalk et al. 2006). Both models were applied to the same site with exact the same data applying the same input factor uncertainties. The graphs illustrate the different behaviour of the two models in two years (2002 and 2003) that can only be revealed if a standardized approach has been used.

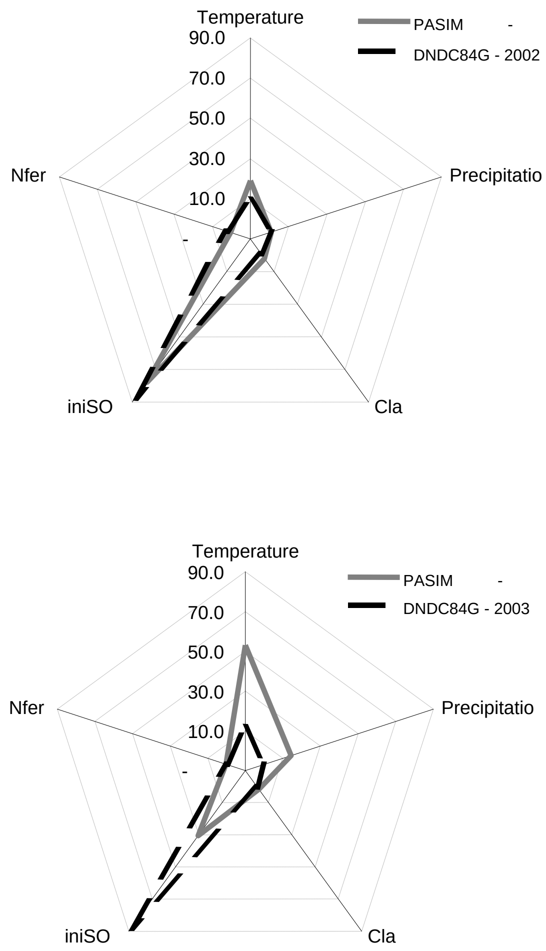

Figure 3. Change of standard deviation of NEE (Net Ecosystem Exchange) in 2002 and 2003 in % for DNDC (black, dashed) and PaSim (grey, solid) attributed to the different input factor uncertainties (Nfert = total nitrogen in fertilizer, iniSOC = initial Soil Organic Carbon)

5. CONCLUSIONS

The presented heuristic approach to develop uncertainty measures helps to ensure a community based adoption of measures and systems. We have used questionnaires to gain expert input to designing these systems, which represents a simple, cost- effective and stake-holder relevant means. The framework we propose allows a high degree of comparability in model experiments. A standardized model framework can enable researchers to access of-the-shelf uncertainty tools to perform *ad hoc* cross-model cross-site comparisons and to evaluate the quality of their own results. The framework allows access to results of cross site cross model experiments for the research community and more importantly, for stakeholder and decision maker. This can be a step towards an ISO standard for uncertainty in model results.

6. ACKNOWLEDGEMENTS

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